Which Ladder to Climb?
Wages of workers by job, plant, and education*

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March 23, 2018

Abstract

How much does your wage depend on what you learned, for whom you work, or what job you do? Using largely unexplored administrative data from Germany allows us to relate 80% of wage variation to observable characteristics of jobs, firms, and workers. One wage determinant stands out: the hierarchy level of a job, summarizing its responsibility, complexity, and required independence. This variable is typically absent in other data sources. Climbing the hierarchy ladder explains almost all of the rise in wage dispersion and half of the wage growth by age. It also is key to explaining gender wage differences.

Keywords: human capital, life-cycle wage growth, wage inequality, careers
JEL-Codes: D33, E24, J31.

*We thank Simon Jaeger, Fatih Karahan, Iourii Manovskii, Esteban Rossi-Hansberg, Michael Waldman, and participants at the REDg meeting 2016, NBER midyear meeting of macro perspectives at Minneapolis, DFG SPP 1764 conferences at Berlin, and the University of Konstanz for helpful comments and remarks. The authors would like to acknowledge the support of the ADEMU project, "A Dynamic Economic and Monetary Union," funded by the European Union's Horizon 2020 Program under grant agreement No. 649396 (ADEMU). Christian Bayer would like to thank the EUI for hosting him while conducting part of the research that led to this paper.

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1 Introduction

How much does your wage depend on what you have learned, for whom you work, or what job you do? And how do the three interrelate? These questions are at the core of human capital theory and key for our understanding of the functioning of labor markets. Their answers shape how we think about education choices, labor market mobility, and earnings differences, and thereby, the optimal design of tax-and-transfer systems, educational institutions, and labor market policies. Finally, as they describe the sources of wage dispersion across individuals, these answers have implications beyond labor markets through the impact of labor-earnings risks on consumption-saving decisions.

We revisit these questions exploiting three waves of administrative linked employer-employee data representative of the German economy and decompose wage growth and rising wage dispersion over the life cycle. Using synthetic panel regressions to control for unobserved heterogeneity (Deaton, 1985; Verbeek, 2008) allows us to identify the causal effect of job and worker characteristics on wages and thereby to estimate how much changes in observable characteristics contribute to wage growth and wage dispersion. We group characteristics so as to represent three components of wages: first, an *individual component* that can change without changing job or employer; second, a *plant component* that will only change with a change in employer; and third, a *job component* that can change over the career of a worker even within a plant.

Differences across plants shape wage dispersion at labor market entry, but it is the job component, in particular a job's complexity, responsibility, and independence, summarized in the hierarchy level of a job, that explains 50% of wage growth and almost all of the rising wage dispersion over the working life. We document large wage differences across hierarchies; for example, climbing the hierarchy ladder from the lowest to the highest level leads to more than a tripling of wages. Differences in progression along the hierarchy ladder are also key to explaining the development of life-cycle gender wage differences. At the beginning of their careers, females have roughly 7% lower hourly wages than males (across all firms and jobs); at the end of their careers that difference is more than 30%. Half of this widening gap is explained by the fact that female career progression drastically slows down around the age of 30, while males continue to climb the hierarchy ladder until age 50. Males and females also differ in the importance of employer differences for wage growth. While 20% of male wage growth over the working life comes from moves to better-paying employers (controlling for worker and job characteristics), females start to move to worse paying employers after the age of 30. This and the lack of career progression of females are likely interrelated because not all employers have the same organizational structure. Well-paying employers offer on average also more jobs at higher levels of hierarchy.

Our database is three waves of the German Survey of Earnings Structure (SES, 2006-2014), large administrative samples that offer linked employer-employee micro data representative for the universe of German employees and employers, working at plants with at least 10 employees. The data contain roughly 3.2 million employee observations (roughly 10% of all employment) in each of the first two waves (a third thereof in 2014). An important feature of the data is that they are directly obtained from plants' human resources departments. Measurement error on all characteristics can therefore be expected to be particularly low. The data report the actual (virtually uncensored) pay and hours worked of employees. They include detailed information on workers' education, occupation, age, and tenure. In addition, they provide a description of the complexity, responsibility, and independence of an employee's job, coded as five levels of "hierarchy." Taken together, all information on jobs, employers, and workers explains over 80% of the observed cross-sectional variation in wages, whereas other data sources mostly allow us to explain one-third of wage dispersion by observables.[1] Detailed information both on employers and on the hierarchy levels of jobs is equally important for explaining the cross-sectional variation, but even when used as the single and only explanatory factor, i.e., without any other information, five hierarchy levels explain more than 45% of wage variation.

Our key finding that climbing the hierarchy ladder is key for wage growth and increasing wage dispersion during the working life sheds new light on the question of the specificity of human capital in the labor market. Our results point to strong job specificity that is determined by the organizational structure of an employer. This organizational structure is independent of workers so that a high-paying (highly productive) job persists for the employer but it is lost from the worker's perspective when a match resolves. But experience in a job at a given level of hierarchy is likely pivotal for finding a new job at a comparable level. Regarding the process of human capital accumulation, our result gives a strong hint that those skills that enable workers to climb the hierarchy ladder are the key skills to achieving high life-cycle wage growth. These skills might be partly innate and partly acquired through education, in particular, education toward intellectual independence, analytical thinking, and the ability to make autonomous decisions. In line with this conjecture, we find that workers with academic training make substantially faster career progress on average.

[1] Although this is a high explanatory power, it is not exceptional and is also found for other administrative linked employer-employee data (see, for example, Strub et al., 2008).

A further result of our analysis regards the importance of plants in explaining the evolution of wage growth and wage inequality over the life cycle. We find that taking into account hierarchy information diminishes the importance of fixed plant differences as a determinant for wage growth and the growth of wage dispersion. This stands in stark contrast to what explains the increase in inequality over *time* (Song et al., 2015). We highlight a new channel through which plants are, in fact, important because jobs of different levels of hierarchy are not evenly distributed across plants. Differences in organizational structure across plants correlate with plants' average pay. In general, plants paying well on all levels of hierarchy also offer more jobs with high levels of responsibility and independent decision making.[2]

We also provide evidence based on the National Compensation Survey (NCS), a representative employer survey for the United States, that our results extend beyond Germany and likely apply to most labor markets in industrialized countries. Job level information in the NCS matches closely the hierarchy information in our data. Job levels explain a large part of wage variation in the cross-section and even within occupational groups in the US, too.

The remainder of the paper is organized as follows: Section 2 puts our results into perspective by reviewing the related literature. Section 3 introduces the data set on which our analysis is based. Section 4 reports the results on the decomposition of wage growth and rising wage inequality. The key finding is that some workers taking up more responsibilities over their lifetime is key for both wage growth and wage dispersion. Section 5 discusses which factors predict these careers. Section 6 provides a robustness and sensitivity analysis. First, we show that hierarchy levels are also a major determinant of US wages (Section 6.1). Second, we ask how our finding that jobs, not plants, are key for wage growth changes when we do not use the hierarchy information (Section 6.2), showing that plants are substantially different in the types of jobs they offer and as such are important for wage dynamics. Section 7 concludes. An appendix follows.

[2]In fact, when job characteristics are ignored, plants appear to be more important in explaining both average wage increases and the life-cycle profile of inequality. In other words, high-paying plants are high-paying because of their job composition rather than some other intrinsic characteristics of the plant. Hence, the average human capital in the plant determines its average wage level. On top comes the utilization of the human capital; even fundamentally high-paying plants have a larger fraction of jobs in higher levels of hierarchy, better-paying occupations, or other characteristics that more intensely utilize the human capital of an employee.

2 Related literature

Our paper focuses on exploring the sources of wage growth and inequality over the life-cycle. In doing so, we pick up a long-standing economic research agenda, going back at least to the seminal work of Mincer (1974), that has evolved in a large literature that has documented patterns of life-cycle wage growth and inequality, for example, Deaton and Paxson (1994), Storesletten et al. (2004), Heathcote et al. (2005), and Huggett et al. (2006). One part of this literature interpreted the residuals from Mincer-style wage regressions as wage risk and estimated stochastic processes to describe this risk. Examples are Lillard and Willis (1978), MaCurdy (1982), Carroll and Samwick (1997), Meghir and Pistaferri (2004), and Guvenen (2009). These estimated risk processes have become a key building block of macroeconomic models with heterogeneous agents. Recently, Huggett et al. (2011) and Guvenen and Smith (2014) took more structural approaches to explore the drivers of life-cycle inequality. A defining feature of all of these papers is that rising life-cycle inequality results mainly from an unfolding stochastic process with persistent idiosyncratic shocks. We add to this literature by relating this stochastic process to observables, in particular, steps on the hierarchy ladder and differences between employers. The latter relates our work to Low et al. (2010) and Hornstein et al. (2011), who explore employer differences as a source of wage inequality in the context of search models.

Employer differences also feature prominently in a different strand of the literature that investigates the sources of rising wage inequality over time. Card et al. (2013) provide a particularly relevant example as they look at the case of Germany. They apply the approach developed by Abowd et al. (1999) to four time intervals of German social security data covering the period from 1985 to 2009. While rising worker differences and the covariance with firms are most important in explaining rising wage inequality, rising firm differences are also a significant contributor. Song et al. (2015) construct an impressive new data set from social security records in the US to study rising earnings inequality for the period from 1980 to 2015. They also apply the approach by Abowd et al. (1999) to different time intervals and find that between-firm differences are the important driver of rising earnings inequality. Song et al. (2015) and Card et al. (2013) both argue that changes in the organizational structure of firms is likely the driver of rising between-firm pay differentials. This explanation would be in line with recent evidence for Germany in Goldschmidt and Schmieder (2017), who document the importance of organizational changes from domestic outsourcing for wage changes especially in the lower part of the wage distribution.

Our findings also echo the literature on internal labor markets and career dynamics within firms. Our analysis differs in its focus from the existing studies, since we look at the importance that hierarchies and employers have for wage growth and the increase in inequality over the life-cycle. Baker et al. (1994) provide a fascinating case study of hierarchies, careers, and internal labor markets. They document large wage differences across hierarchy levels, and they show that few hierarchy levels —six in their case— suffice to represent the organizational structure of the firm and that five hierarchy dummies explain 70% of the wage variation within this single firm. Absent promotions across hierarchy levels, they find virtually no individual wage growth for workers over time, and importantly for our analysis, they also provide evidence contradicting the idea of reverse causality in the sense that hierarchies are determined based on wage levels. Dohmen et al. (2004) provide another fascinating case study on the aircraft manufacturer Fokker that corroborates the key findings from Baker et al. (1994) for our analysis.

For theoretical models in this strand of the literature, Waldman et al. (2012) provide an excellent overview. At the center of his discussion are the seminal papers by Lazear and Rosen (1981) explaining promotion dynamics as a result of tournaments and by Waldman (1984) emphasizing the signaling role of promotions in an environment with asymmetric information about worker ability. Lazear and Rosen's work (1981) is of particular interest for our analysis because they provide a theory as to why rank-order wage schemes exist in firms, i.e., wage schemes where wages do not depend on worker's output but on the worker's hierarchy level in the firm. While the model in Waldman (1984) shares the feature of a rank-order wage scheme, it emphasizes potential inefficiencies from promotion dynamics under asymmetric information.

The organizational structure of firms is the focus of the model in Caicedo et al. (2018) that explicitly incorporates hierarchies into the production process. In the model, a relative shift of the worker-skill to the production-task ("problem") distribution explains rising wage inequality of the magnitude observed in the data. Importantly, the change in wage inequality in the model results from the endogenously changing organizational structure. Reduced-form empirical models like that of Abowd et al. (1999) would likely pick this up by changing firm fixed effects and their covariance with worker effects. Closely related is the paper by Caliendo et al. (2015), who study a sample of French manufacturing firms. They find that an organizational structure with four layers of hierarchy explains up to 66% of within-firm wage variation. They provide empirical support for the theoretical model in Garicano and Rossi-Hansberg (2006) by exploring the dynamic evolution of hierarchies and wage structures when firms grow and shrink. In our analysis, we will also explore the link between organizational structure and firm wage differentials in detail. One difference with the existing literature is that we explore the life-cycle dimension of careers in terms of hierarchy.

3 Data

We use data from the 2006, 2010 and 2014 waves of the Survey of Earnings Structure ("Verdienststrukturerhebung"), henceforth SES, for our analysis. The SES data are an administrative representative survey of establishments (short: plants). The survey is conducted by the German Statistical Office and establishments are legally obliged to participate in the survey so that selection due to non-response does not arise. The data are employer-employee linked and contain establishment-level and employee-level information. Establishments with 10 to 49 employees have to report data on all employees. Establishments with 50 or more employees report data only for a representative random sample of employees. Small establishments with fewer than 10 employees are not covered by the data (prior to 2014). The data also contain information about an establishment's employment share of the total employment of the firm to which it belongs. We exploit this information to study also single plant firms in a sensitivity analysis. Data on regular earnings, overtime pay, bonuses, hours worked, both regular and overtime, are extracted from the payroll accounting and personnel master data of establishments and directly transmitted via a software interface to the statistical office. Transmission error is therefore negligible.

The data cover public and private employers in the manufacturing and service sectors. Self-employed workers are not covered. In total, the data have information on roughly 28,700 establishments with about 3.2 million employees (in 2006, similarly in 2010, a third thereof in 2014). The data are representative of 21 million workers in Germany.

3.1 Sample selection

For our baseline, we restrict the data to workers whose age is 25 to 55. After having estimated the effect of observables, we split the sample by males and females when analyzing the life cycle because male and female career paths differ substantially, as we show. We drop very few observations where earnings are censored,[3] and all observations for which the state has a major influence on the plant (75,016 employee observations in 2006, for example).[4] Our wage measure is monthly gross earnings including overtime

[3]The censoring limit is 1,000,000 € in 2006 and 750,000 € since 2010 in annual gross earnings. We impose the latter throughout.

[4]For a large set of observations this information is missing. The information is only available if in a region-industry cell there are at least 3 firms in which the state has a major influence. Major influence is

pay and bonuses divided by regular paid hours and overtime hours. Since we use plant fixed effects, all observations are dropped where our sample selection by age leaves us with fewer than 10 workers at a plant.

3.2 Job complexity, responsibility, and independence: The hierarchy variable

Importantly and different from many other data sources, our data distinguish among five levels of hierarchy in describing the job of a worker. These hierarchy levels are defined based on the complexity of a job (skill and typical educational requirements), the responsibility (for one's own work or the work of others), and the independence (the decision making power) associated with a job.[5] The lowest level is workers who perform simple tasks (*untrained workers, UT*). The tasks for these workers typically do not require particular training (such as an apprenticeship) and can be learned on the job in less than 3 months. The second level (*trained workers, TR*) covers tasks that require some occupational experience but no full occupational training (apprenticeship). Tasks performed at this hierarchy level can be typically learned on the job in less than 2 years. Workers at the two lowest hierarchy levels do not undertake any decisions independently. Only from the third level of hierarchy onwards do employees have some discretion regarding their work. Jobs at the third hierarchy level (*assistants, AS*) typically require a particular occupational training (apprenticeship) and in addition occupational experience. Workers at this level prepare decisions or take decisions within narrowly defined parameters. An example would be a tradesman, junior clerk, or salesman. These typically decide on everyday business transactions (e.g., a sale) and thus have some discretion. Yet, they are not responsible for the work of others or do they decide on tactics or strategy of the business. The fourth hierarchy group works on tasks that typically require both specialized (academic or occupational) training and experience (*professionals, PR*). Importantly, they perform their tasks independently, they have substantial decision-making power over their cases/transactions/organization of production, and they have some decision-making power in regard to the work of others. Typically, these workers oversee small teams (examples would be foremen in production, junior lawyers, heads of office in administration). The fifth hierarchy level is managers and supervisors (*management, MA*). Their primary task is strategic decision making, which requires high levels of independence and comes with substantial responsibility regarding the work of others.

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defined as being a government agency, the state owning 50+ percent share, or due to other regulations.

[5] We discuss below similarities to modern occupational codes.

Table 1: Summary statistics for wages and hierarchies in the SES 2006 - 2014

	Wages (in 2010 €)					Pop. Sh. of Hierarchy (in %)					
	Av.	Gini	p10	p50	p90	UT	TR	AS	PR	MA	N. Obs
Males											
2006	20.5	0.26	10.5	18.0	32.8	5.8	17.0	43.4	24.3	9.5	707,490
2010	20.2	0.28	9.8	17.5	33.3	7.6	17.7	41.5	22.2	10.9	597,764
2014	21.2	0.27	10.3	18.3	34.8	5.5	13.9	45.9	23.3	11.3	192,557
Females											
2006	15.9	0.22	8.7	14.7	23.8	12.5	18.9	46.2	18.6	3.9	431,449
2010	15.7	0.24	8.4	14.4	24.1	13.8	17.8	45.5	18.1	4.8	359,112
2014	16.6	0.24	8.7	14.9	25.8	9.6	15.3	51.4	18.1	5.7	127,295

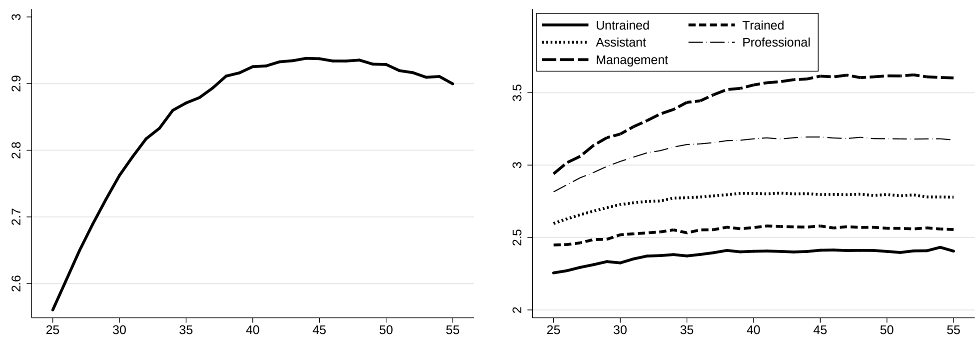
Notes: "Wages" refers to the hourly wages in constant 2010 prices. "Av." is the average and "p10/50/90" are the 10/50/90-percentile of the wage distribution, respectively. "Pop. Sh. of Hierarchy" refers to the population share of a hierarchy level in the sample population, where "UT/TR/AS/PR/MA" are untrained, trained, assistants, professionals, and managers respectively. "N. Obs." refers to the unweighted number of observations in the final sample (age 25-55, no public employer).

Importantly, hierarchy is neither an educational nor an occupational concept, though both are related to hierarchy. Appendix A provides details on this along with more detailed information on the definition of the hierarchy variable. We discuss the role of education for career progression along the hierarchy dimension in Section 5.

3.3 Descriptive statistics and trends

Table 1 reports the number of observations for each wave as well as information on average wages and wage inequality within our main sample. We report real wages in constant 2010 prices using the German CPI deflator. The average real hourly wage is roughly €20 (€16) for men (women) and has not grown much since 2006. Median real wages have been falling from roughly €18.0 in 2006 to €17.5 in 2010 for males and returned to €18.3 in 2014. Female median real wages have fallen from €14.7 to €14.4 between 2006 and 2010 and then grown again to €14.9. This means that female wages are roughly 20% lower than male wages on average. Wage inequality has increased somewhat for both genders between 2006 and 2014 and is higher among men. The p90/p10-ratio went up from 3.1 to 3.4 for males and from 2.7 to 3.0 for females.

Figure 1: Wage by age and hierarchy level



(a) All workers (b) Workers by hierarchy

Notes: The left panel shows the average (log) real wage by age over all workers and sample years. The right panel shows mean (log) real wage by age and hierarchy levels. Year fixed effects have been removed.

In addition, Table 1 reports the population shares of workers at the five different levels of hierarchy. The share of male workers (values for females in brackets) with high or very high independence in decision making (MA+PR) has slightly shrunk from 33.5% (22.2%) to 32.5% (21.9%) over the three waves. The share of male (female) workers that have autonomy only within very clearly defined limits, i.e. only in how they carry out a given task or with respect to the substance of the question they need to decide (AS), has increased from 43.8% (46.6%) to 48.2% (54.0%) (females in brackets), while the share of male (female) workers that have no autonomy at all (TR+UT) went down from 22.8% (31.2%) to 19.3% (24.1%).

In the data, the average wage of an employee increases substantially in age. The average wage of a worker increases by roughly 2% with every year of age between age 25 and age 45 and levels off afterward. Yet, this average wage increase masks substantial heterogeneity. Figure 1 reports the mean log wage difference to age 25 by age conditioning in addition to hierarchy levels. We find that the top hierarchy group always has the highest wage and sees the strongest increase in wages with age, so that the wage differences between the top level and the other groups widen with age. For example and reading age differences as if they were life-cycle profiles, a worker constantly remaining at the *assistant* hierarchy level will have a 20 log point (= 22%) increase in his/her wage over his lifetime, roughly half the average wage increase, while at the management level, wages rise by 80 log points (123%), roughly twice the average increase. A worker climbing up the career ladder from a job as an untrained worker to a management-level job will see a stellar 120 log points (232%) increase in his/her wage over his/her lifetime.

This suggests that moving up the hierarchy ladder might be an important contribution to life-cycle wage growth. Other potential contributions to wage growth could be the effects of occupational mobility, mobility toward better-paying plants, further formal education, or pure returns to experience. The next section decomposes wage growth over the life cycle into the contribution of each of these components.

For this decomposition, it is key that the SES data are exceptional in that the worker and plant characteristics can explain more than 81% of wage variation in the cross-section if we use plant fixed effects. Even without plant fixed effects but with plant-level controls, 63% of wage variation in the cross-section can be explained, see Table 5 in Appendix A.2. Part of this high explanatory power is due to the high quality of the data. A second part comes from, as we will show later, the fact that the data contain information about hierarchy levels of jobs.

4 The life cycle of wage growth and wage inequality

To understand the factors that contribute to wage growth and wage inequality over the life cycle, we estimate the effect of various plant, job, and worker characteristics on wages. We deal with the challenge of unobserved heterogeneity by using synthetic panel methods. A simple OLS estimator of, for example, the impact of a jobs' hierarchy levels on wages might be inflated because more able workers obtain higher wages at any job and are also more likely to end up on higher hierarchy levels. The synthetic panel methods exploit the fact that aggregation of the micro data to a cohort level creates a panel structure (see Deaton, 1985; Verbeek, 2008, for an overview of the method).

4.1 Methodology

To be specific, assume that log wages w_{ipt} of individual i working at plant p at time t are given as

$$w_{ipt} = \gamma_i + \zeta_{pt} + \beta_J J_{it} + \beta_I I_{it} + \epsilon_{ipt} \tag{1}$$

where J_{it} is the characteristics of the job of the individual, I_{it} is the characteristics of the individual itself, γ_i is the worker fixed effect, and ζ_{pt} is the effect of plant p at time t. This means that $\beta_I I_{it}$ captures the wage effect of worker characteristics that can change without changing job or plant, the *individual component*. Specifically, we use education and age as dummies by sex.[6] The *job component*, $\beta_J J_{it}$, captures the characteristics of a job that can change without changing plants. Here, we use dummies for two-digit occupations and dummies for the hierarchy level of a job.

Since we do not have panel information on workers, but only repeated cross-sections, we cannot directly control for unobserved heterogeneity from worker fixed effects. Therefore, we construct a synthetic panel, defining cohorts of workers by sex, birth year and regional information (North-South-East-West) and aggregate to the cohort level.[7] To control for plant effects, we first demean all variables at the plant level and drop plants with fewer than 10 observations to obtain

$$\hat{w}_{it} := w_{ipt} - w_{.pt} = \hat{\gamma}_i + \beta_J \hat{J}_{it} + \beta_I \hat{I}_{it} + \hat{\epsilon}_{it}, \tag{2}$$

where $\hat{X}_{it}$ denotes the difference between variable X_{ipt} for worker i and its average $X_{.pt}$ at the plant where this worker is working. Thereafter, we aggregate to the cohort level and obtain

$$\hat{\hat{w}}_{ct} = \hat{\hat{\gamma}}_c + \beta_J \hat{\hat{J}}_{ct} + \beta_I \hat{\hat{I}}_{ct} + \hat{\hat{\epsilon}}_{ct}, \tag{3}$$

where $\hat{\hat{X}}_{ct}$ denotes the average of $\hat{X}_{it}$ within a cohort c. We finally use this equation to obtain estimates $\tilde{\beta}_J$ and $\tilde{\beta}_I$ by fixed effects OLS. The minimum observations across cohort-year cells is 424, the maximum is 8397, and the median is 3509. Since we do not observe any cohort over its entire life cycle, the identifying assumption is that the life cycle is stable across cohorts.[8]

Using the estimated coefficients, we then calculate the plant component as wage minus the average individual and job component at the plant. It is given by

$$\tilde{\zeta}_{pt} \quad = \quad w_{.pt} - \tilde{\beta}_J J_{.pt} - \tilde{\beta}_I I_{.pt}. \tag{4}$$

This means that our estimated plant component, ζ_{pt}, corrects the average wage at a plant for differences in organizational structure and work force quality by removing the average individual and job components across plants.[9]

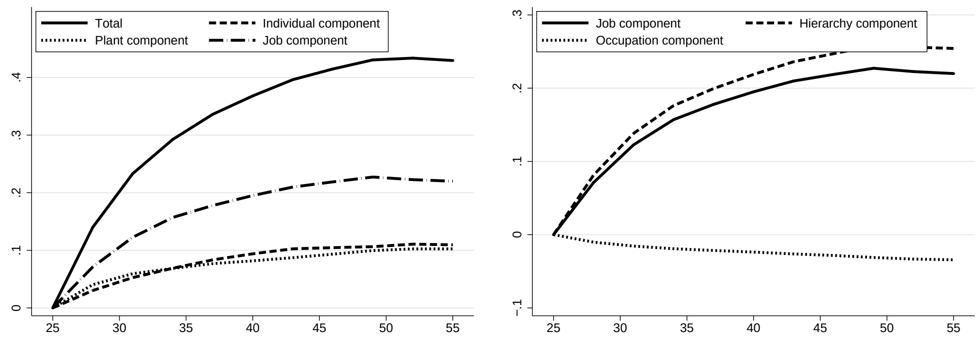
[6] We group ages using three-year windows to identify cohort effects later on, given the four-year distance between the three survey waves.

[7] The annual gross migration rate between German states in the past 30 years is low and has been roughly 1.3% p.a.; see *Wanderungsstatistik* of the *Statistisches Bundesamt*. More than a third of this migration is between states of the same region.

[8] This assumption has to be taken into account when interpreting our results. Male (female) workers of younger cohorts work more (less) part-time and are less (more) likely to participate in the labor market than a generation before.

[9] This implies that the plant component estimate will capture the average *unobserved* heterogeneity of workers within a plant, too. Consequently, the estimators for the various components are consistent if

Figure 2: Wage and job component decomposition (males)



(a) Wage (b) Job component

Notes: Left panel: Decomposition of log wage differences by age relative to age 25 for male workers. The dashed line corresponds to the individual, the dotted line to the plant, and the dashed-dotted line to the job component; the solid line (total) equals the sum over the three components. Horizontal axis shows age and vertical axis shows log wage difference. Right panel: Decomposition of job component (solid line) into the contribution of occupations (dotted) and hierarchies (dashed). The graphs show the coefficients of age dummies of a regression of the components on a full set of age and cohort dummies (ages defined as 3-year groups).

4.2 Wage growth

Next, we use the estimates of the individual, job, and plant components to decompose the life-cycle profiles of wages. We calculate the average wage and the three components for all workers in an age-year cell and then regress these averages on a full set of cohort and age dummies. We report the coefficients on the age dummies as our life-cycle profiles, always normalizing the log wage of a 25-year-old to zero in the following figures.

We decompose the wage growth of male and female workers separately. The reason is that, as we will see, these decompositions show very distinct patterns because males and females have different career paths over their life cycle. We first look at males, discuss female workers in the second step, and compare career paths in a third step.

4.2.1 Males

Our first set of results regards average wage growth for males. Figure 2(a) reports the decomposition of mean log wages into its components. On average, wages of men grow by ca. 45 log points over the life cycle.[10] The job component alone can explain around 50%

there is no assortative matching in unobserved plant and worker heterogeneity. If matching is positively (negatively) assortative, the plant effect tends to be positively (negatively) biased. As part of the robustness checks, we estimate the plant component based on observable plant characteristics only. Results are similar, except that the variance of wages explained by plant differences is smaller.

[10]The difference in the descriptive analysis by age as in Figure 1 stems from cohort effects.

of wage growth by age. Moving to better-paying plants over the life cycle contributes to slightly more than 20% of wage growth. The remainder, the individual component, captures pure experience effects.

Within the job component, it is promotions along the hierarchy dimension that are key to explaining average wage growth, as Figure 2(b) shows. In fact, movements across occupations contribute slightly negatively to wage growth, controlling for hierarchy levels. In turn, most of the life-cycle wage growth results from workers taking on jobs with increasing degrees of responsibility, complexity, and independence over the course of their careers. We explore the relation between tenure with the same employer and education and steps on the career ladder in Section 5.

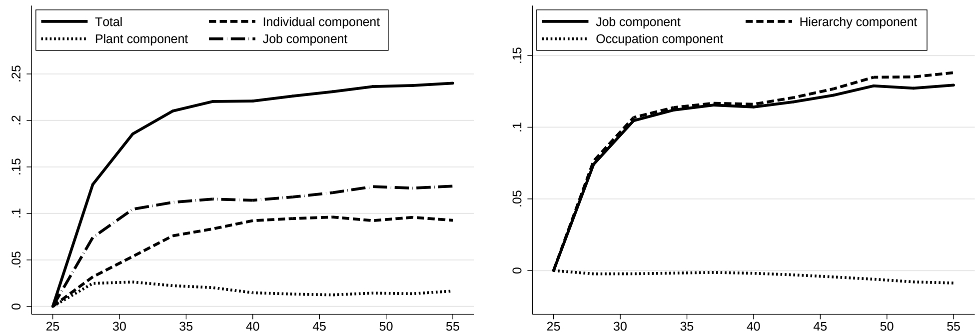
4.2.2 Females

Female and male labor market performance is known to differ along many dimensions. Average wages of females are lower and grow less over the life cycle. Key for this is, as our decomposition shows, the smaller increase in the job component, in particular, the slower move up the hierarchy ladder; see Figure 3(a). Female wages grow over the life cycle only by 25 log points, compared to 45 log points for males. The job component still accounts for the lion's share (12 log points), but, compared to males (22 log points), the average female career is substantially flatter. One reason is that between age 30 and age 45 there is virtually no growth in the job component. As for males, the job and hierarchy components are virtually identical. The individual component for females shows a smaller increase, too, compared to men. Interestingly, the plant component shows a decreasing profile after the age of 30. One reason could be that the non-wage aspects of a plant, such as its location, play more important roles for females than males after family formation.

4.2.3 Comparing male and female careers

The result of these different career paths is that males and females earn significantly different wages in the German labor market. Already at labor market entry (age 25), females in our sample earn a roughly 7% lower hourly wage than males. This is close to the official estimate of the residual gender pay gap but, as a raw average, may still contain occupational and employer differences. At the age of 50, females earn wages that are more than 30% lower than wages for males. Figure 4(a) highlights how important differential careers along the hierarchy ladder are for the widening of the gender wage gap over the life cycle. It shows the job component from Figure 2 (males) and Figure

Figure 3: Decomposition of wage and job component (females)



(a) Wage

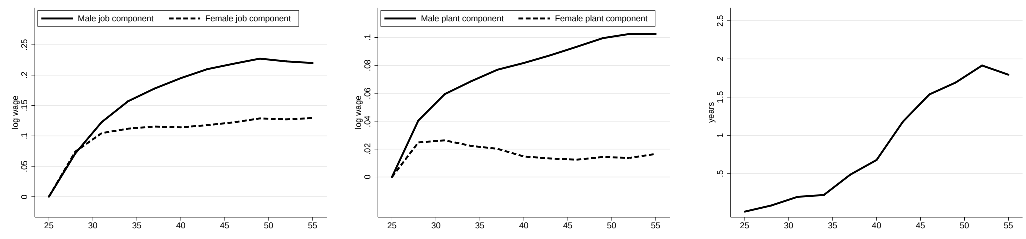
(b) Job component

Notes: Decomposition of average wages of female workers, otherwise see Figure 2

3 (females). Up to age 30, males and females experience an identical increase in the job component. After age 30, the career progression of females comes to a halt, while males keep on climbing the career ladder for an additional 10 to 15 years. The result is an additional 10 log point wage difference between males and females at the age of 50. This is almost half of the increase in the gender wage gap over the life cycle. Close to all of the remaining 10 log points difference in wage growth between male and female employees comes from differences in mobility across plants. While males continuously move to plants that pay better on average, females after the age of 30 tend to sort into plants that pay worse; see Figure 4(b). The different dynamics of employer mobility by females also shows up in employer tenure by age. Figure 4 (c) shows mean tenure by age for males and females after controlling for cohort effects. Until their mid-30s, males and females have only a small difference in tenure of about 4 months. This difference increases strongly afterward, and up to age 55, it has grown to almost 2.5 years. This highlights again the diverging pattern of males and females starting after the first 10 years in the labor market, whereby females seem to end up in lower levels of hierarchy, at worse paying plants, and with less stable jobs.

Interpreting these results as life-cycle facts and therefore extrapolating to the expected life-cycle profiles for younger cohorts of women should be taken with a grain of salt. Our sample spans 9 years and the estimated life-cycle pattern also comes from comparisons across cohorts.

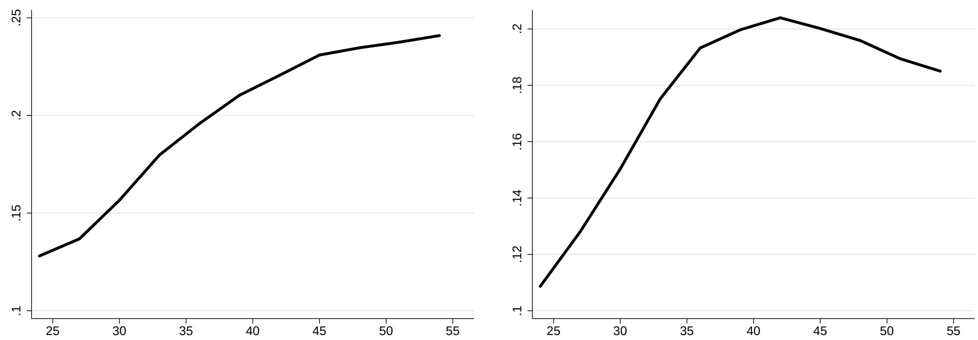
Figure 4: Job and plant component of males and females



(a) Job component (b) Plant component (c) Tenure difference

Notes: (a) Job component from decomposition of mean log wages for males and females. (b) Plant component from decomposition of mean log wages for males and females. Both: Horizontal axis shows age and vertical axis shows log wage difference. (c) Difference in average years of tenure of male and female workers.

Figure 5: Variance of log wages by age (raw data)



(a) males (b) females

Notes: Variance of log wages for males and females. Left panel shows males. Right panel shows females. Horizontal axis shows age and vertical axis log wage variance.

4.3 Wage inequality

It is a well-documented fact that wage and earnings inequality increases substantially over the life cycle. Figure 5 shows the variance of log male and female wages by age without taking any cohort effects into account. We find the typical pattern of an almost linear increase in the cross-sectional variance for males. For females, the pattern is similar until their early thirties and flat thereafter. Again, we first discuss males, then females.

4.3.1 Males

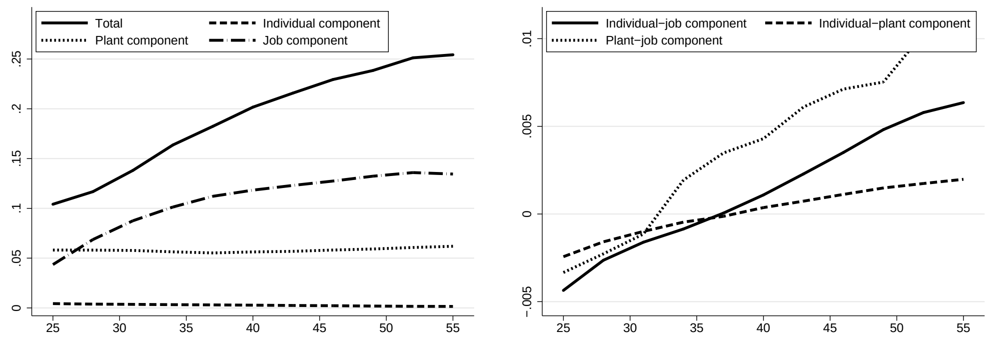
The variance of log-wages for men increases substantially over the life cycle: by 12 log points over 30 years. Bayer and Juessen (2012) find a comparable number for average household wages taken from SOEP data from Germany. Heathcote et al. (2010) report for the US an increase between 17 and 20 log points over the same part of the working life. Most existing micro data explain about 30% of the observed wage inequality by observables. The largest part of wage inequality remains unexplained. Consequently, the largest part of wage inequality is interpreted as the result of idiosyncratic risk captured by a stochastic process in microfounded models of consumption-savings behavior (see Heathcote et al., 2014, to give one example).

Given the high degree of statistical determination in our data, we can go beyond the scope of existing studies and shed new light on the determinants of wage inequality. We next explore the contribution of each component to wage dispersion.

In Figure 6(a) we display the life-cycle profile of wage dispersion controlling for cohort effects. Relative to the raw data in Figure 5, the profile becomes somewhat steeper. Over the life cycle, the variance of log wages of workers increases from roughly 10 log points to 25 log points. The variance of the plant component contributes to wage dispersion with a constant 7 log points. The job component, by contrast, shows an increase in its variance from 4 to 14 log points. In words, two-thirds of the total increase in wage variance is coming from workers becoming increasingly different in the type of job they perform. As for average wages, the hierarchy level of the job is the main driving variable. The variance of the individual component is by construction virtually zero: education remains mostly constant over the working life and hence does not affect the wage dispersion within an age-cohort cell.

There are two remaining components unreported in Figure 6(a): the variance of what is not explained and the sum of all covariance terms of observables. Figure 6(b) shows the covariance terms by splitting the covariance into components due to covariances between the job, individual, and plant components by age. We find that the covariance terms are mostly close to zero on average. Yet, they show a non-negligible life-cycle pattern. In particular, the covariances between the firm and job component and between the individual (education) and the job component increase over the life cycle. In words, young workers who are in high levels of hierarchy tend to be at low-paying plants and tend to have lower levels of education. When workers age, workers at high levels of hierarchy are found more often in plants that pay well on average and are most likely to have high degrees of formal education.

Figure 6: Variance-covariance decomposition (males)



(a) Variance (b) Covariance

Notes: Left panel: Decomposition of the variance of log wages by age for male workers. Variances of all components are calculated by age-cohort cell. The solid line is variance of total wage, dashed line the individual, dotted line the plant, and dash-dotted line the job component. Right panel: Covariance components for variance decomposition calculated analogously to the left panel; the solid line refers to the covariance of the individual and job component, the dashed line to the covariance of the individual and plant component and the dotted line to the covariance of the plant and job component; all covariances are within the age-cohort cell. All graphs show the coefficients of age dummies of a regression of the variance-covariance components on a full set of age and cohort dummies (ages defined as 3-year groups).

The sum over all covariance terms increases from -1 log point to slightly below 2 log points over the life cycle. This means that the covariance terms contribute another 6 log points increase to the log wage variance over the life cycle (twice the difference between the two covariance terms). This is equal to the wage dispersion increase not explained by the job component alone. To summarize, the dispersion in the job component and the covariance of the job, plant, and individual components explain all of the increase in wage dispersion over the life cycle.

In turn, we conclude that the residual wage dispersion shows no life-cycle profile. The absence of any slope in the residual component is consistent with transitory i.i.d. wage shocks over the life cycle. It is clearly not consistent with a large persistent component in a stochastic process of residual wage risk that is non-related to career progression. Conversely, our results suggest that the source of persistent wage shocks is the progression or the absence of progression along the hierarchy ladder.

However, this does not mean that it does not matter for whom one works. The job-plant covariance is slightly positive on average and increasingly so over the life cycle. This means that well-paying plants also offer more opportunities for career progression later in life. That the correlation is negative early in life means that workers who start their careers at well-paying plants start there at the bottom of the hierarchy ladder but later face ample opportunities for career progression. We further explore the implications of the plant-job correlation for the inference about and the importance of plants in more detail in Section 6.2.

4.3.2 Females

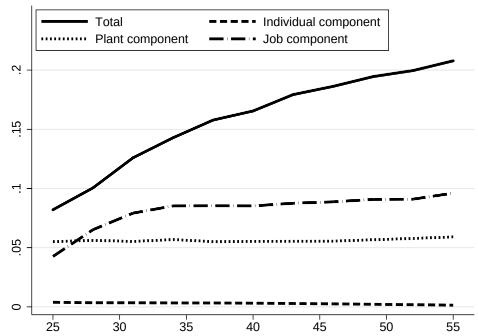
We have seen that women have flatter careers on average after age 30. This also has implications for wage inequality among women. Their wage dispersion grows less in age; see Figure 7(a). In particular, the increase in hierarchy dispersion is much smaller in age for women than for men and levels off after age 30. Still, the life-cycle profile in the job component explains 50% of the 12 log point increase in wage dispersion over the working life of females (compared to 15 log points increase in variance for males). For females, we also find a flat life-cycle profile in the plant component. At the same time, the job-plant covariance profile is even steeper for women than for men. Those women who end up in high levels of the hierarchy at the end of their working life work in high-paying plants. Yet, from Figure 4 we know that later in their working life, fewer women tend to work in high-paying plants than at the age of 30. Plainly put, it seems that selection into careers is stronger for women than for men.

5 Who makes a career?

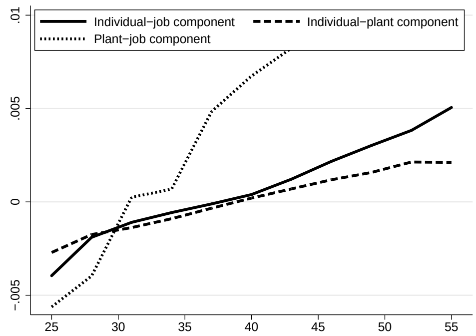
Given the importance of careers, i.e., moving up the hierarchy ladder, we next shed some light on the question of how important labor market experience and eduction are for a career. Workers at higher levels of hierarchy are both typically older and better educated; see Table 2. Figure 8 displays how many more years of tenure a five-years-older age group has compared to the preceding. We calculate this number by hierarchy level to characterize how job stability changes with age and hierarchy. The figure shows that workers at higher levels of hierarchy tend to have more stable employment histories and increasingly so over their careers.

All of these characteristics - mobility, education, and experience - pick up some form of past investment in human capital. As a result, they are correlated, and therefore, we want to estimate their effects on hierarchy in a regression. Since hierarchies have a meaning in terms of log-wages, we can use their estimated coefficients to measure the distance between hierarchy groups, such that we end up with a cardinal measure of hierarchy: the wage that is typically associated with it. Then, constructing the hierarchy

Figure 7: Variance-covariance decomposition (females)



(a) Variance



(b) Covariance

Notes: Decomposition of the variance of wages of female workers, otherwise see Figure 6.

wage of a worker as we did before and aggregating these hierarchy wages back to the cohort level, we use this generated variable to estimate the causal effect of an employee's characteristics on his/her moving up the hierarchy ladder.[11]

For this purpose we specify the average hierarchy wage hw_{ct} of a cohort c at time t as a function of that cohort's educational attainment, work experience, and tenure with its current employer. We use the average fraction of a cohort over the three sample years that has academic, vocational, or no training (as well as the fraction for which education information is missing) as a measure of educational attainment and interact this with experience. We estimate the following model:

$$\begin{aligned} hw_{ct} &= \gamma_c + tenure_{c,t} + tenure_{c,t}^2 \\ &\quad + experience_{c,t} * (1 + education_c + gender_c) + \varepsilon_{ct} \end{aligned} \tag{5}$$

The baseline effect of education on hierarchies is then not identified separately from the cohort effect, but we can understand whether education leads to steeper or flatter career profiles. We estimate for young, middle aged, and experienced workers separately to allow for career slopes that vary with age. For comparison, we also calculate the estimates from a pooled cross-sectional OLS regression.

The right panel of Table 3 reports the results of the synthetic panel regression. The

[11] Given the ordinal nature of hierarchy data, an ordered probit estimator would have been an alternative approach. Yet, given that we have to resort to synthetic panels in order to control for unobserved heterogeneity, this is not straightforward, because the probit model is non-linear.

Table 2: Share of hierarchy levels within formal education and age groups

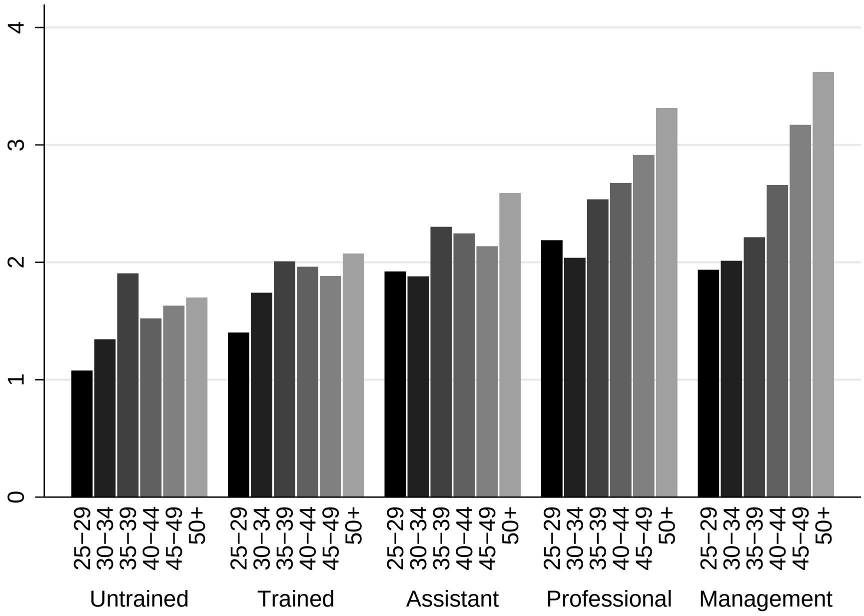
Education	at age 25 - 35 (in %)					at age 35 - 45 (in %)				
	UT	TR	AS	PR	MA	UT	TR	AS	PR	MA
Males										
Secondary	25.4	38.1	26.8	7.7	2.0	18.2	39.9	29.7	9.2	3.0
Vocational	5.5	15.9	60.6	15.6	2.5	3.5	12.9	52.4	24.5	6.7
University	1.2	2.9	27.5	48.6	19.9	0.4	1.2	13.9	44.9	39.7
not reported	17.7	29.6	38.1	11.9	2.7	12.6	28.0	36.1	16.1	7.2
Females										
Secondary	29.9	31.5	28.0	8.8	1.8	34.8	35.9	21.4	6.1	1.8
Vocational	5.7	13.1	64.2	15.2	1.9	6.3	13.8	57.2	19.8	3.0
University	2.0	4.6	35.1	40.3	18.1	0.9	2.9	25.1	43.8	27.3
not reported	20.1	24.7	42.4	10.8	2.0	26.9	26.1	33.7	10.5	2.9

Notes: Relative frequencies across hierarchy groups in percentage points for different age groups. Top part of the table shows male workers, bottom part female workers. Shares sum within age groups to 100. Secondary education contains all workers with secondary education but no vocational training. Vocational education refers to workers with secondary education and in addition a vocational degree. University degree refers to all workers with a university or technical college degree. Workers without reported education are in group not reported. Hierarchy groups UT/TR/AS/PR/MA refer to untrained, trained, assistants, professionals, and managers, respectively.

left panel of the table reports the results from a pooled cross-sectional OLS regression. The latter does not control for unobserved heterogeneity but allows us to estimate the baseline effects of education and not only heterogeneous experience slopes. Both workers without training and workers with academic training show steeper career paths than workers with only vocational training. We find that workers without training or unknown education enter the labor market on average at lower levels of hierarchy than workers with vocational training; see Table 2 and the OLS results. One interpretation of the steeper career path for less educated workers in the cohort fixed effects regression is that they are catching-up in the sense that low educated workers profit from work experience, in particular when young, exactly because they lack the formal vocational training.

On the other side of the distribution, workers with academic training enter at higher levels of hierarchy, but then their careers further diverge from the workers with vocational training and this divergence accelerates later in life. The size of this divergence trend is substantial. On average workers with academic training see a 5-8 log point higher

Figure 8: Tenure gradient by age and hierarchy



Notes: The figure displays the average additional years of tenure of an age-group relative to the preceding one by hierarchy level. Averages over all sample years, both males and females. For 25-29-years-olds the figure shows the average number of years of tenure in the group.

annual wage growth due to career progression than workers with vocational training. As we have seen before, females have flatter career profiles in their thirties than males. The difference between males and females is insignificant early and late in their career.Job tenure shows a positive coefficient. That is, workers in higher levels of hierarchy have been with the same firm longer, even controlling for age and education.

Table 3: The effect of experience, education, and tenure on career progression

	Pooled Cross Section OLS			Cohort Fixed Effects		
age group	25-30	31-40	41-55	25-30	31-40	41-55
experience	1.1***	0.6***	-0.2***	2.8**	0.5	-1.7***
× female	-0.3***	-0.7***	-0.1***	-0.3	-0.6***	-0.1
× academic training	2.0***	0.7***	0.1***	3.7	2.1	6.9***
× only secondary education	-0.3***	-0.8***	-0.0	15.9***	6.2**	5.2***
× unknown education	0.4***	-0.3***	-0.3***	-9.0**	-0.3	4.9***
tenure	1.5***	1.2***	0.8***	7.3***	3.0***	2.5***
tenure^2	-0.5***	-0.3***	-0.1***	-8.0***	-1.6***	-0.6***
female	1.7***	3.0***	-6.7***			
academic training	24.8***	31.8***	41.4***			
only secondary education	-12.8***	-10.4***	-21.0***			
unknown education	-8.2***	-4.5***	-3.6***			
Cohort fixed effects	No	No	No	Yes	Yes	Yes
Observations	360,844	740,054	1,314,769	180	300	450
Adjusted R^2	0.20	0.25	0.29	0.84	0.79	0.96

Notes: *,**,*** indicate significance at the 10, 5, and 1 percent level, respectively. The left panel displays the regression coefficients of a regression of the hierarchy wage of a worker on tenure and experience interacted with the educational attainment of the worker and on education dummies. The left panel displays the results of a regression of the cohort-year average log hierarchy wages on tenure and experience interacted with the average educational attainment of a cohort controlling for cohort fixed effects; see equation (5). Log-Wages have been multiplied by 100 to ensure better readability. The baseline group is male workers with occupational training. We control for different male/female career profiles by including an experience gender interaction term. Cohorts are defined by birth year, gender and region (North/South/East/West).

6 Robustness

6.1 Hierarchies in the US labor market

It could be that the importance of hierarchies is particular to the German labor market with its prevalence of collective bargaining agreements. Relative to this, the US labor market is a polar-opposite case with only a very small minority of workers being covered by collective bargaining. For this reason and to check the robustness of our findings, we look at US data from the National Compensation Survey (NCS) run by the Bureau of Labor Statistics and provide evidence that strongly suggests that our results on the importance of hierarchies generalize. We think that the reason for this is that hierar-

Table 4: Mean wages in 2015 by job level and occupational group

	Occupational groups (SOC)					
Level	11-29	31-39	41-43	45-49	51-53	All
All	38.22	12.58	17.34	23.09	17.87	23.25
1		8.55	9.63		10.01	9.25
2		9.63	10.53	14.26	12.09	10.48
3	13.01	11.15	12.83	14.78	15.62	12.89
4	15.42	13.67	16.32	18.23	19.67	16.39
5	18.80	18.84	20.14	21.11	20.95	20.13
6	20.96	21.83	24.42	27.47	24.92	23.77
7	24.63	28.03	30.56	30.67	31.27	27.17
8	32.11	33.14	38.82	34.12		32.92
9	37.50		62.13			38.32
10	42.68					44.55
11	50.65					53.26
12	69.37					73.13

Notes: Mean wages by job level and occupational groups from the 2015 National Compensation Survey. Occupational groups follow the 2010 SOC codes. The different occupational groups correspond roughly to Management, Business & Finance, IT & Engineering, Education, Legal, Healthcare (11-29), Service (31-39), Sales and Administration (41-43), Farming, Construction, Maintenance (45-49), Production and Transportation (51-53). See SOC classification for further details. Missing fields indicate the case of too few observations for combination of job level and occupational group to be reported by the BLS. These estimates are currently not published by the BLS and have been provided by the BLS upon request.

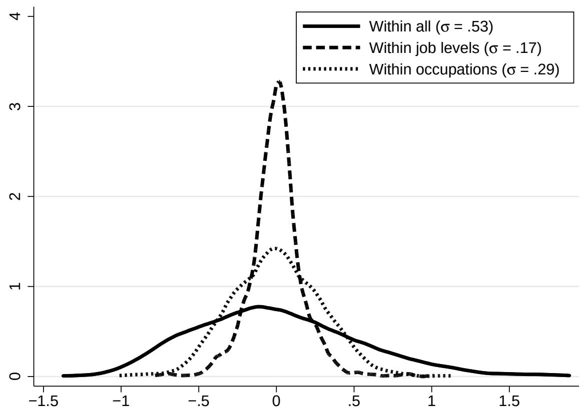
chies arise naturally in the organization of work (Garicano and Rossi-Hansberg, 2006; Caicedo et al., 2018) and compensation schemes based on job leveling are commonly used in the labor markets of industrialized countries.[12]

The BLS provides detailed information that describes the job-leveling procedures in the data. Its job leveling is distinct from its occupational coding,[13] although some of the information used for the occupational coding and for job leveling overlaps; see Appendix

[12]In fact, job leveling is an entire industry in which consulting firms provide employers with tools to rank jobs and implement compensation schemes for jobs at different levels. One famous example is the point system developed by the Hay Group.

[13]Occupational classification schemes like the SOC used by the BLS differentiate jobs according to the tasks but not according to the level of complexity, so that occupational codes do not imply a hierarchical ordering but a horizontal differentiation.

Figure 9: Wage density across occupations by job level



Notes: Kernel density estimates for within-group wage dispersion of log mean full-time wages. Solid line shows dispersion within all full-time workers. Dashed line shows within-job-level dispersion and dotted line within-occupation dispersion. Legend reports standard deviations. All data come from the 2010 National Compensation Survey. See text for further details.

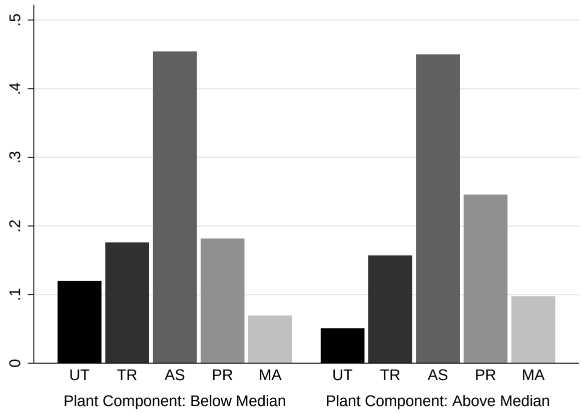
B for details. We provide corresponding evidence based on the German occupational coding (KldB) discussed in Appendix A.2.

The NCS provides information on average wages by job level both across and within occupations. Table 4 shows mean wages by job level and occupational groups from the 2015 NCS.[14] We see that within coarse occupational groups there is a very large variation in wages across job levels. We also note that the first occupational group (11-29), which includes management occupations and has on average much higher wages than the other groups, actually has lower wages than the other occupational groups once we condition on job levels. Vice versa, the relative wage differences across occupations are conditional on a job level typically small and (with one exception) less than 20%.

For 2010, we have more disaggregated occupational information for wages by job level. In total there are 15 job levels and 307 distinct occupations. We use these data to compare the dispersion within a job level across occupations, within occupations across job levels, and the distribution across all job-level-occupation combinations. Since we do not observe the number of employees, we treat each occupation-job-level pair as one observation. Figure 9 shows the estimated kernel densities for the three distributions. We find that the wage dispersion conditional on the job level is strongly compressed relative to the unconditional wage dispersion and also relative to the wage dispersion conditional

[14]These estimates are currently not published by the BLS and have been provided by the BLS upon an individual request for data.

Figure 10: Shares of employees by hierarchy level and plant component



Notes: The figure shows the share of workers by hierarchy group in plants with below or above median estimated plant component $\tilde{\zeta}_b$. The median is defined on a worker basis. 67% of all plants have a below median plant component.

on occupations. The standard deviation of wages decreases by 45% conditioning on 307 occupations and by 68% conditioning on only 15 job levels relative to the unconditional standard deviation; again see Figure 9.

We conclude that conditional on the job level, a large part of the observed unconditional occupational wage differences disappears, which suggests that the importance of hierarchies (job levels) also applies to the US labor market. Similarly, we find that our results are robust if we condition only on plants not covered by collective bargaining in the German data; see Appendix C.1.

6.2 The (un)importance of plants

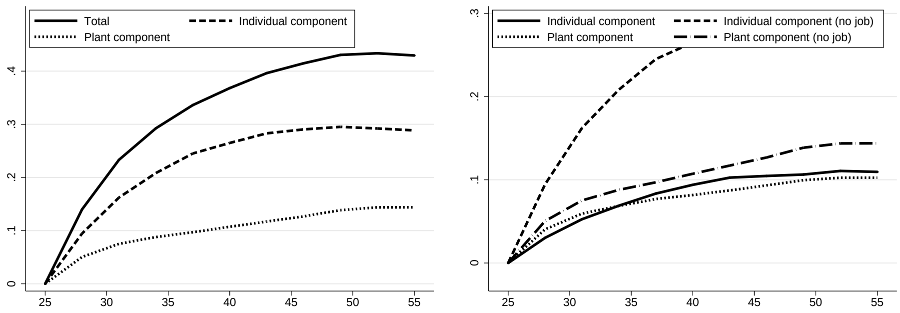
One result of our analysis is that the plant component does not contribute much to wage dispersion growth over the life cycle. At the same time, recent evidence for the US finds increasing firm differences to be a key driver of the increase in wage inequality over the past 30 years (Song et al., 2015). At a first glance, these two pieces of evidence do not seem to align well. However, we have seen that the plant component and the job component are positively correlated and increasingly so over the life cycle of a worker. This implies that the plant component will pick up the organizational structure of plants, too, if we do not include information about this structure in the analysis.

Figure 10 reports the share of jobs at various levels of hierarchy for jobs sorted by the plant component ζ_p. Well-paying plants offer on average more jobs at higher levels of hierarchy; only low-paying plants offer a substantial fraction of jobs on the lowest two hierarchy levels. Note for this figure we sort plants according to whether they pay better *at all levels* of hierarchy, i.e., the plant component is not driven by having a larger share of top-level workers. Well-paying plants are on average also substantially larger. In turn, the bottom 50% of jobs by plant component are in the bottom 67% of plants.

In turn, decomposing wages ignoring the terms that go into the job component leads to a pattern that is different from our baseline that includes this information. First, a substantially larger fraction of wages remains unexplained. More important, throwing away the job information leads to an overestimation by roughly 30% of the role of mobility between plants for wage growth, as Figure 11 shows. Similarly, the contribution of plants to the wage inequality is inflated by 50% and both education and mobility across plants become important contributors to the increase in wage dispersion over the life cycle; see Figure 12. Together, the individual and plant components explain roughly 8 out of the 15 log point increase in the wage variance. The covariance between the individual and plant components also contributes to the growth of wage inequality by 2 log points (not displayed). This means that, without job information, residual wage inequality has a life-cycle profile, contributing another 5 log points to the increase in wage dispersion. This is in stark contrast to what we find when we include the job information, where residual wage inequality is both negligible and has a flat life-cycle profile.

In summary, this means that plants are important for life-cycle wage dynamics, but not because of their wage level differences but because of their differences in organizational structure whereby different plants offer different career paths. These differences in organizational structure are correlated with average plant pay and get partly picked up by the plant component when organizational structure is unobserved.

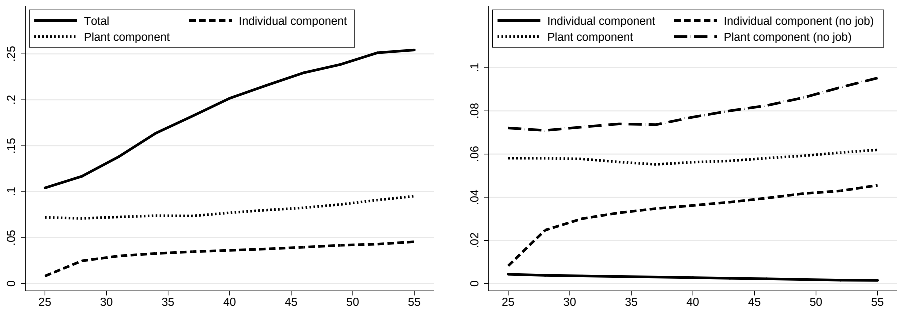
Figure 11: Decomposition of mean wage by age (males), ignoring job information



(a) decomposition (b) comparison

Notes: See Figure 2 for the left panel. The right panel displays the corresponding components from Figure 2 (a) for comparison.

Figure 12: Decomposition of variance of wages by age without job controls (males)



(a) decomposition (b) comparison

Notes: See Figure 6 for the left panel. The right panel displays the corresponding components from Figure 6 (a) for comparison.

7 Conclusions

The present paper analyzes wage data from the German Survey of Earnings Structure. We find that both wage growth and the increase in wage dispersion over the life cycle can be well explained by observable characteristics of jobs, plants and workers. In particular, the responsibilities, independence, and complexity of a job, the job's hierarchy level, is the most important factor. Tertiary education seems particularly important to prepare workers for jobs at the top hierarchy levels as workers with academic training on average progress faster along the career ladder. Mobility between employers does not contribute to career progression.

This has a broad range of implications. For example, educating future workers in the ability to take responsible decisions has likely high returns and is key for structural transformation. In fact, well-paying plants seem to have shorter spans of control of top-level workers and more workers who need less supervision. Similarly, our findings suggest that changes in organizational structures within firms may be important in our understanding of wage inequality and its developments over time.

From the individual's perspective, our results imply that career progression and job search also within firms is key to understanding wage risks. Residual wage risk that cannot be linked to any observables is small and has a flat life-cycle profile once the hierarchy information of jobs is taken into account. This further suggests that persistent wage risk is related to other macroeconomic factors, such as structural change. Similarly, it suggests that the average life-cycle wage growth and wage dispersion are linked because both result from career progression. This further suggests that wage risk differs across individuals. In particular, male and female workers show both different average wage growth and different wage dispersion after the age of 30, when female career progression slows down substantially.

At an aggregate level, our results raise the question of how many congestion externalities organizational structures generate: even when a worker might be qualified for a job further up the hierarchy ladder, that job may already be filled. In turn, we conclude that plants are important through their difference in organizational structure, which implies that plants differ vastly in the career opportunities they offer. At the same time, differences in pay across plants that are not related to job characteristics seem to be a minor contributor to wage growth and do not contribute at all to the increase in wage dispersion over the life-cycle. This suggests that the plant-related differences in pay are known to workers and therefore workers do not need to search for higher wages across plants. Instead, the lacking age profile in the dispersion of the plant component suggests that the differences are compensating differentials.

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A Further details on the German SES data

A.1 Data collection and explanatory power of observables

The wage data in the German SES are transmitted to the statistical offices directly – and in most cases automatically – from the human resources and payroll accounting departments of firms. Therefore, the data contain very little measurement error. For that reason, and mostly because we observe the hierarchy level of a worker, explanatory variables have high explanatory power; see Table 5. The table shows the R^2 statistics from a descriptive regression of log worker wages on various sets of observables. Both, hierarchies and plants are important in explaining wage dispersion. What stands out, however, is that five levels of hierarchy can explain close to 46% of wage variation. At the same time, we see that the R^2 of a regression that combines both plant and hierarchy effects is smaller than the sum of the R^2 statistics of the separate regressions. This reflects the important correlation between plants and hierarchies we have documented.

Table 5: Importance of characteristics in explaining hourly wages

	Plants	Hierarchies	Hierarchies and plants	Hierarchies, plants, occupations, education, experience, tenure, and sex	Hierarchies, plant size, collective bargaining, region, and industry
(adj.) R^2	0.581	0.459	0.779	0.812	0.625

Notes: Adjusted R^2 of different regressions on log wages. All regressions contain year fixed effects as additional regressors. First column regression only on plant fixed effects, second column only on hierarchy dummies, third column on hierarchy dummies and plant fixed effects, the fourth column on hierarchy dummies, plant fixed effects, occupation dummies, education, experience, tenure, sex, and interaction dummies, and the fifth column on hierarchy dummies, plant size dummies, dummy for collective bargaining,regional dummies, and industry dummies.

A.2 Additional details on the hierarchy variable

In the German data, the hierarchy variable is coded in five levels. Hierarchical concepts are of course also prevalent in collective bargaining agreements and hence there is a mapping from job descriptions in collective bargaining agreements to the hierarchy variable in our data. Typically collective bargaining agreements have more detailed job descriptions and job leveling.

Relatedly, hierarchy levels are associated with a typical education level. Education is, however, neither a prerequisite for any hierarchy nor do all workers with a certain education work at a given hierarchy level or above. The hierarchy classification captures a functional concept within an establishment, not a qualification concept. Hence, hierarchy, while correlated with formal education is a job- (i.e. task-)specific concept, while education captures past investments in human capital. As we have seen from Table 2, a substantial fraction of workers is employed at all hierarchy levels for virtually any level of formal education (with the exception maybe of extreme combinations) and that workers progress along the hierarchy dimension as they get older, both of which clearly indicates that formal education and the hierarchy variable measure two distinct concepts.

It is also important to note that hierarchy classification is distinct from the occupational classification of jobs. Hierarchy levels vertically distinguish jobs in terms of their complexity and decision-making power. Occupational classifications distinguish workers horizontally by the type of task that is done. One example is the 3-digit occupation "food preparation": within this occupation there can be different hierarchy levels capturing the differences between dishwashers, kitchen assistants, commis, chefs de partie, and sous and head chefs. In addition, measures of occupation seem to be plagued with measurement error in many survey data sets, e.g., the CPS (see, e.g., Kambourov and Manovskii, 2013), which we can expect to get stronger the higher the level of disaggregation. Having said this, the recent revisions of 5-digit occupation codes have started to measure and encode job complexity (Helper/Trained/Specialist/Expert) (ISCO-08 or KldB-2010 for Germany). Table 6 shows a cross-tabulation of the last digits of the occupational classification system KldB2010 of the German employment agency against a job's hierarchy information. While the two are positively correlated, there is still a substantial mass off diagonal.

Table 6: Cross-tabulation of hierarchy measured directly and hierarchy inferred from occupation codes

Complexity measured by occupation	Fraction of occupation (in %)	Fraction of hierarchy within occupation (in %)				
		UT	TR	AS	PR	MA
All	100	6.4	13.4	50.1	19.9	10.4
from last digit (KldB 2010)						
Helper	13.4	29.6	40.4	27.4	2.0	0.6
Trained	55.6	4.0	13.2	69.2	11.3	2.4
Specialist	15.8	0.7	2.9	35.8	50.9	9.6
Expert	15.2	0.5	1.1	14.7	34.7	48.9
using management occupations (KldB 2010)						
Supervisors	2.3	0.9	3.3	32.8	42.1	20.9
Managers	2.9	0.6	1.3	15.9	30.5	51.6

Notes: Cross-tabulation of hierarchy and job information provided by the German Statistical Office based on data from the 2014 Survey of Earnings Structure. Occupational information extracted from 5-digit occupational code (KldB 2010). First part of the table (*last digit*) shows the distribution of workers by occupational complexity across hierarchy groups. Shares sum to 100 within each row. First column (*total*) shows population share of occupation group. Second part of the table (*management occupations*) shows distribution of occupations coded as supervisors or managers across hierarchy groups. Shares sum to 100 within each row. Numbers in column total refer to share of workers coded as supervisors or managers in the total population.

B Additional details on the hierarchy variable in the US National Compensation Survey

The US National Compensation survey classifies all jobs according to their occupation and their job level. Occupations are coded using the Standard Occupational Classification (SOC) system based on the skill levels and primary duties. For the job leveling, the BLS interviewers evaluate the duties and responsibilities of a job. The method used to classify jobs is *point factor leveling* and it assigns points to particular aspects of the duties and responsibilities of the job. It also takes into account the skills, education, and training required for the job. Hence, there is some overlap with occupation codes. In contrast to the occupation coding, the job leveling aims to evaluate jobs with respect to required knowledge, job controls and complexity, contacts on the job in terms of nature and purpose, and a job's physical environment. Jobs are evaluated for each of these four factors and the job level is the sum of level points from all four factors. Importantly, the job leveling is based on responsibility and not on assigned job titles in establishments.

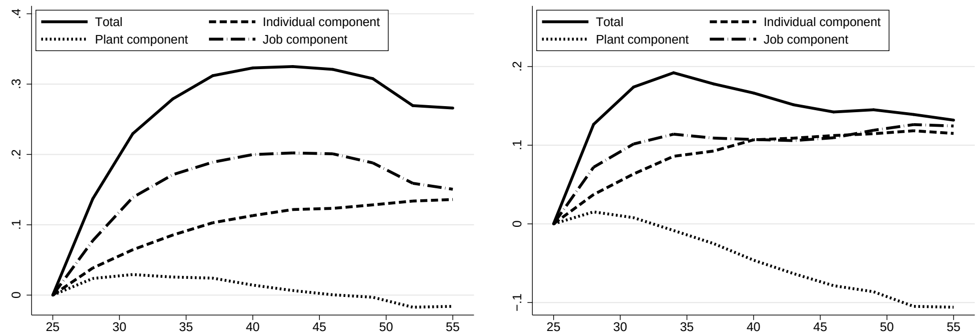
The BLS then groups jobs in up to 15 job levels. See the US Bureau of Labor Statistics (2013) Job Level Guide for further details.

C Robustness checks and further material

C.1 Plants without collective bargaining

As a robust analysis, we consider in this section only plants that are not covered by a collective bargaining agreement.

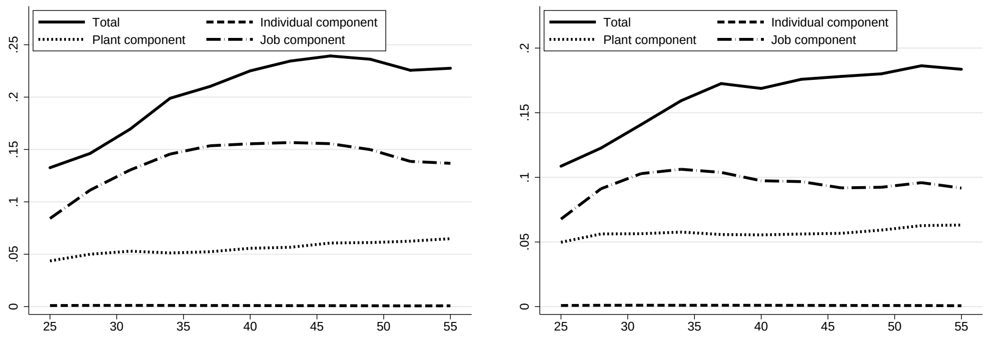
Figure 13: Wage decomposition for plants not covered by collective bargaining



(a) Males (b) Females

Notes: Decomposition of log wage differences by age relative to age 25 for male (left panel) and female (right panel) workers. Sample restricted to workers who work in plants not covered by collective bargaining agreement. The dashed line corresponds to the individual, the dotted line to the plant, and the dashed-dotted line to the job component; the solid line (total) equals the sum over the three components. Horizontal axis shows age and vertical axis shows log wage difference. The graphs show the coefficients of age dummies of a regression of the components on a full set of age and cohort dummies (ages defined as 3-year groups).

Figure 14: Variance-covariance decomposition for plants not covered by collective bargaining



(a) Males

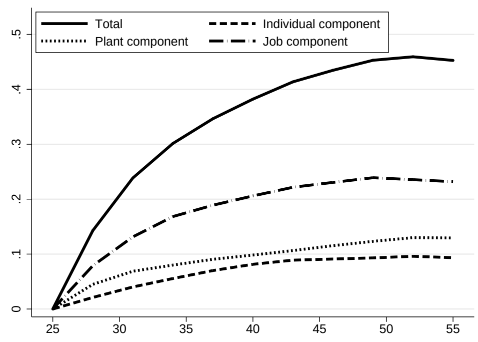
(b) Females

Notes: Decomposition of the variance of log wages by age for male (left panel) and female (right panel) workers. Sample restricted to workers who work in plants not covered by collective bargaining agreement. Variances of all components are calculated by age-cohort cell. The solid line is variance of total wage, dashed line the individual, dotted line the plant, and dash-dotted line the job component. All graphs show the coefficients of age dummies of a regression of the variance-covariance components on a full set of age and cohort dummies (ages defined as 3-year groups).

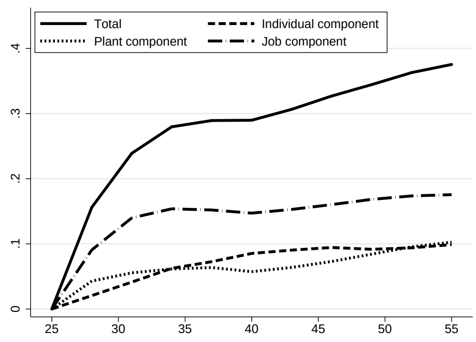
C.2 Only full-time employees

As a robust analysis, we consider in this section only workers who work fulltime where full-time is defined as 35 hours per week and 35 $\times$ 4.25 hours per month. A 35-hours workweek is since 1995 the regulation for full-time employment in several West German industries.

Figure 15: Wage decomposition for full-time workers



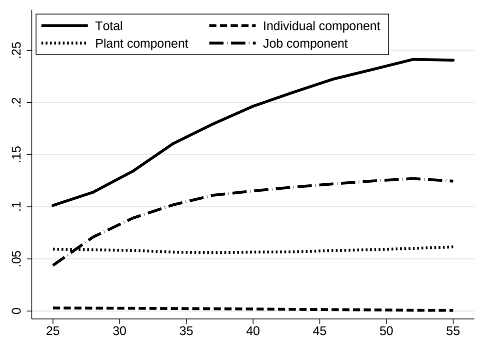
(a) Males



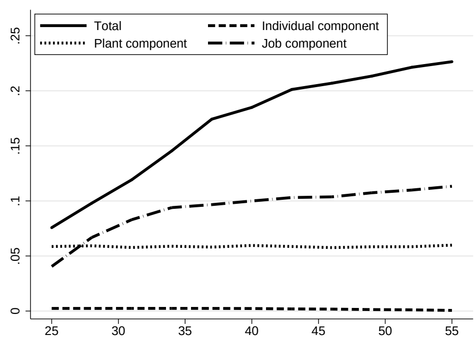
(b) Females

Notes: Decomposition of log wage differences by age relative to age 25 for male (left panel) and female (right panel) workers. Sample restricted to full-time workers. The dashed line corresponds to the individual, the dotted line to the plant, and the dashed-dotted line to the job component; the solid line (total) equals the sum over the three components. Horizontal axis shows age and vertical axis shows log wage difference. The graphs show the coefficients of age dummies of a regression of the components on a full set of age and cohort dummies (ages defined as 3-year groups).

Figure 16: Variance-covariance decomposition for full-time workers



(a) Males



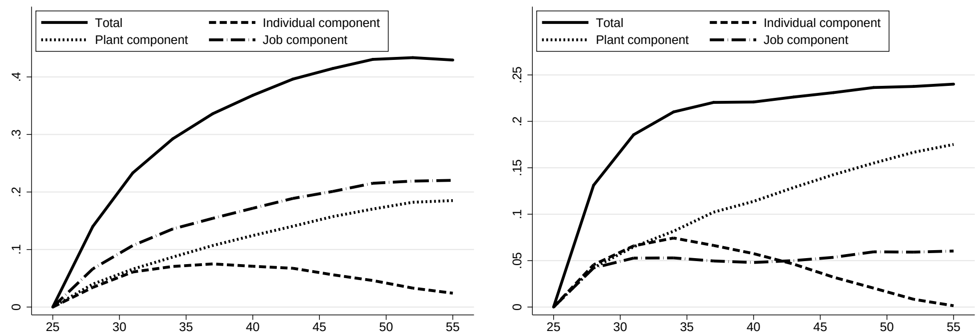
(b) Females

Notes: Decomposition of the variance of log wages by age for male (left panel) and female (right panel) workers. Sample restricted to full-time workers. Variances of all components are calculated by age-cohort cell. The solid line is variance of total wage, dashed line the individual, dotted line the plant, and dash-dotted line the job component. All graphs show the coefficients of age dummies of a regression of the variance-covariance components on a full set of age and cohort dummies (ages defined as 3-year groups).

C.3 Using plant characteristics instead of plant fixed effects

In the main part of the paper, we construct the plant component as residual wage component after controlling for worker and job composition. As a sensitivity check, we use here plant controls to construct the plant component. We include in the regression dummy controls for the number of employees at the plant, a dummy indicating if the plant is covered by a collective bargaining agreement, and dummies for industries. We proceed otherwise as in the main part of the paper.

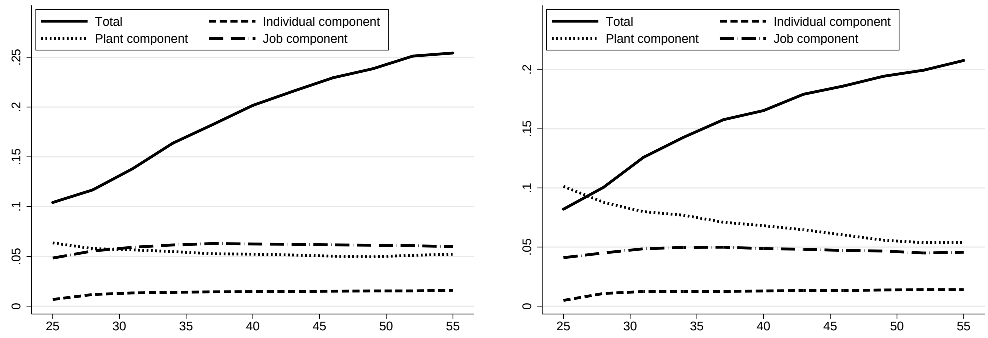
Figure 17: Wage decomposition using plant controls



(a) Males (b) Females

Notes: Decomposition of log wage differences by age relative to age 25 for male (left panel) and female (right panel) workers. Plant component constructed using controls for dummies for number of employees, dummy for collective bargaining agreement, and industry dummies. The dashed line corresponds to the individual, the dotted line to the plant, and the dashed-dotted line to the job component; the solid line (total) equals the sum over the three components. Horizontal axis shows age and vertical axis shows log wage difference. The graphs show the coefficients of age dummies of a regression of the components on a full set of age and cohort dummies (ages defined as 3-year groups).

Figure 18: Variance-covariance decomposition using plant controls



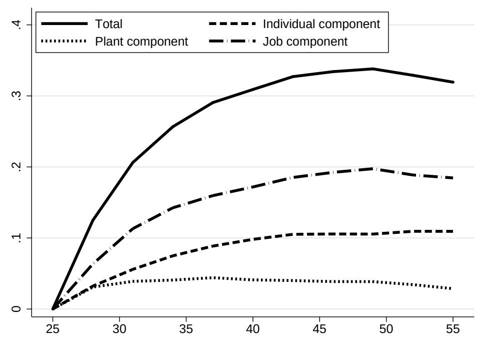
(a) Males (b) Females

Notes: Decomposition of the variance of log wages by age for male (left panel) and female (right panel) workers. Plant component constructed using controls for dummies for number of employees, dummy for collective bargaining agreement, and industry dummies. Variances of all components are calculated by age-cohort cell. The solid line is variance of total wage, dashed line the individual, dotted line the plant, and dash-dotted line the job component. All graphs show the coefficients of age dummies of a regression of the variance-covariance components on a full set of age and cohort dummies (ages defined as 3-year groups).

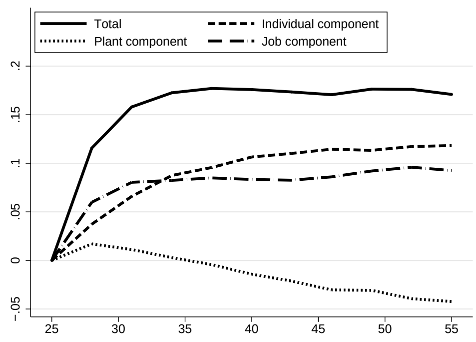
C.4 Small and large plants

As a robust analysis, we consider in this section workers in small and large plants separately. We define a plant to be small if it has less than 250 employees and large if ti has 250 or more employees. For 2006 we can also look at the employment share of a single plant in the firm. We find that small plants are also overwhelmingly single-plant firms. The average employment share of a small plant in the firm is 89%, the median is 100%, and the 25th percentile are 97%. For large plants, the share is smaller indicating that more of them are part of multi-plant firms. We find the plant at the 75th percentile of the employment share distribution accounts for 99% of firm employment so that about a quarter of large plants are single-plant firms. On average a large plant accounts for 66% of employment of the firm and the median is 85%.

Figure 19: Wage decomposition for workers in small plants



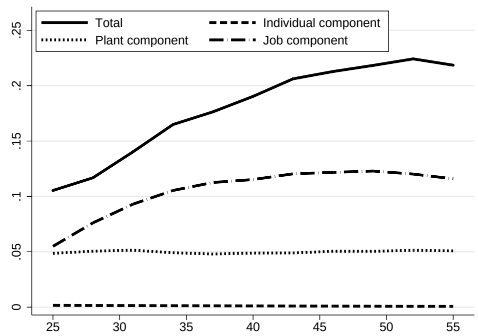
(a) Males



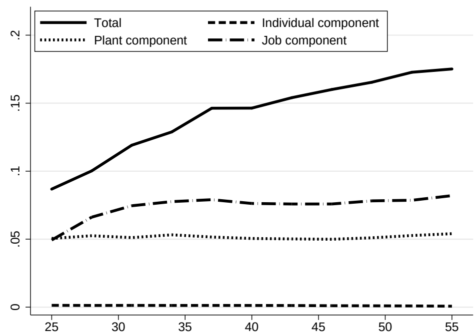
(b) Females

Notes: Decomposition of log wage differences by age relative to age 25 for male (left panel) and female (right panel) workers. Sample restricted to workers in small plants (less than 250 employees). The dashed line corresponds to the individual, the dotted line to the plant, and the dashed-dotted line to the job component; the solid line (total) equals the sum over the three components. Horizontal axis shows age and vertical axis shows log wage difference. The graphs show the coefficients of age dummies of a regression of the components on a full set of age and cohort dummies (ages defined as 3-year groups).

Figure 20: Variance-covariance decomposition for workers in small plants



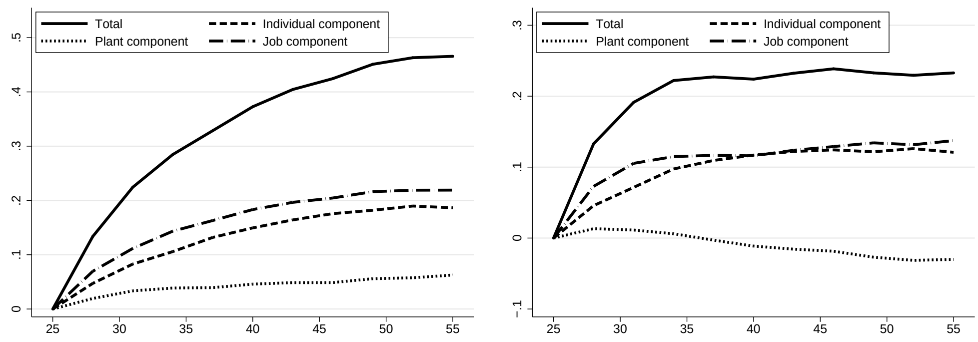
(a) Males



(b) Females

Notes: Decomposition of the variance of log wages by age for male (left panel) and female (right panel) workers. Sample restricted to workers in small plants (less than 250 employees). Variances of all components are calculated by age-cohort cell. The solid line is variance of total wage, dashed line the individual, dotted line the plant, and dash-dotted line the job component. All graphs show the coefficients of age dummies of a regression of the variance-covariance components on a full set of age and cohort dummies (ages defined as 3-year groups).

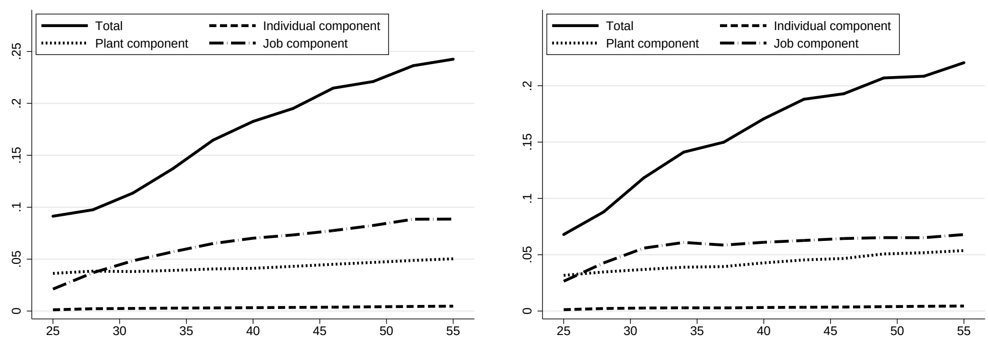
Figure 21: Wage decomposition for workers in large plants



(a) Males (b) Females

Notes: Decomposition of log wage differences by age relative to age 25 for male (left panel) and female (right panel) workers. Sample restricted to workers in large plants (250 employees and more). The dashed line corresponds to the individual, the dotted line to the plant, and the dashed-dotted line to the job component; the solid line (total) equals the sum over the three components. Horizontal axis shows age and vertical axis shows log wage difference. The graphs show the coefficients of age dummies of a regression of the components on a full set of age and cohort dummies (ages defined as 3-year groups).

Figure 22: Variance-covariance decomposition for workers in large plants



(a) Males (b) Females

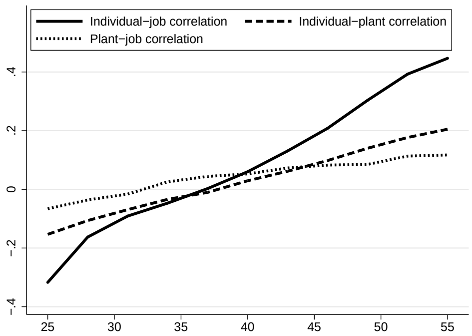
Notes: Decomposition of the variance of log wages by age for male (left panel) and female (right panel) workers. Sample restricted to workers in large plants (250 employees and more). Variances of all components are calculated by age-cohort cell. The solid line is variance of total wage, dashed line the individual, dotted line the plant, and dash-dotted line the job component. All graphs show the coefficients of age dummies of a regression of the variance-covariance components on a full set of age and cohort dummies (ages defined as 3-year groups).

C.5 Further results referenced to but unreported in the main text

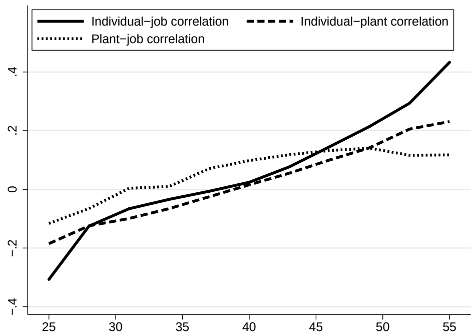
C.6 Correlations

Figure 23 expresses the covariances displayed in 6 (b) and 7 (b) in terms of correlations. The individual component and job component show the strongest life-cycle profile in terms of correlations. This reflects the finding that better educated workers have steeper career paths.

Figure 23: Correlations between individual, plant, and job component



(a) Males



(b) Females

Notes: See Figures 6 (b) and 7 (b). The present figure displays correlation coefficients instead of covariances.